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AN EXPERT BASED INITIAL GENERATION OF GENETIC ALGORITHM WITH ADAPTIVE PROBABILITY APPROACH FOR QUADRATIC OPF

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Abstract: *This paper presents a novel and superior Genetic Algorithm (GA) based resolver for Optimal Power flow (OPF) problem. Here, the main contrast to other Genetic Algorithm based approaches is that a novel expert based initial generation of population and adaptive probability approach (variable Cross over probability and mutation probability) is adopted in selection of offspring together with roulette wheel technique which reduces the computation time and increases the quality considerably. Selection and Placement of Shunt Devices are considered as a variable in this novel approach. Here continuous variables like Voltage Profile and discrete variable like transformer tapings are considered while minimizing the Fuel cost. The results obtained on standard IEEE 14 bus and 30 bus systems is compared with simple Genetic Algorithm and Particle Swarm Optimization (PSO) to Optimal Power flow and is found that this approach is more efficient, robust and promising.*
Keywords: *Adaptive probability, Optimal Power Flow, Genetic Algorithm, Genetic Operators, Power system Optimization.*

1. Introduction

The rapid deregulation and restructuring of power system piloted increased complexity of the network and posed new challenges for a reliable and powerful mathematical modeling and control in Power System Energy Management. The optimal power flow has been attracting the researchers for long and wide use of semiconductor devices and qualms on security and quality of Power has added more shine to it. More over the competitive market looks for more and more profit based business in deregulated scenario and each operator works for maximum profit margins, which cannot permitted at the cost of Social and Environmental aspects which lead to the establishment of central authority and techniques to analyze the status of network. The requirement of an efficient and secure modeling has led to inevitability of Optimal Power flow (OPF) in Power System Operation, Control and Planning in energy management system (EMS).
Optimal Power flow (OPF) is a highly Non-linear, Non-convex, large optimization problem which solves for the best settings of the control variables for optimized Power flow with multiple equality and inequality constraints together with continuous and discrete control variables. Since years, the first approach to OPF has been made by J Carpentair in 1962 and much of the considerable developments are marked in [1-3]. Classical approaches contained 'Newton Method' which suffered from slow convergence at higher roots, 'Gradient Method', 'Linear Programming', 'Mixed Integer Linear Programming' methods which required linearization of the objective function and non-negative control variables by taking incremental changes over an operating point, lead to mediocrity and inferior accuracy. All above methods had difficulty in handling large number of different constraints. 'Non-Linear Programming (NLP)', 'Semi-definite programming', and 'Quadratic programming' emerged as special NLP methods whose objective function is a quadratic equation and constraints are linear functions and 'Decomposition method' is reported in [4]. Much extension of classical methods emerged as 'sequential quadratic programming', 'Sequential linear programming' and 'homogenous linear programming'. The approach based on Non-Linear programming uses the Karush-Kuhn-Tackeroptimality conditions. Later higher models of 'Interior Point Method' (IPM) emerged as predictor–corrector, multiple centrality corrections and non-interior point method based unlimited point algorithm and the complementarity method found to excel more. The 'primal-dual integer programming' of 'Semi-definite programming' has found to the best advantage of not having to calculate the Jacobian and Hessian matrix.
As OPF being multi-model in nature, all these methods had the shortcoming of settling in a local minimum than a global optimal solution and being a much of approximation and dependent on continuous variables, designing with discrete variable became a concern.

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The application of Artificial Intelligence, Meta-heuristics and Evolutionary based solutions emerged to unravel these constraints and much research is being done on Evolutionary methods and in depth Fuzzy modeling and fuzzy mathematical programming has been discussed by V. Miranda et al. and Y. Terasawaet al.(1992).'Artificial Neural Network' based and 'Genetic Algorithm' and much tailored adaptations of it have been discussed in Section IV. Meta-heuristics based Optimization proved to be an another prospective option and various natural observable facts were mimicked like the animal flocking and 'fish schooling' and'Particle swarm Technique', the way the ants communicate, transfer and store food was impersonated to build as 'Ant colony' based OPF, and imitate how the metals gets annealed and the revisions from a hot metal to a strong Cold meal developed in 'Simulated Annealing'&'Tabu Search Algorithm'. Much comparison of the optimization methods has been marked in [5] and a good comparison of AC and DC power flows can be found in [6].

Further, growth of Power systems have opened a new domain, where consumer not only look for uninterrupted power, but also for the quality of the power, lead to Introduction of security constraints to maintain the system in secure mode free from contingencies and lead to the prerequisite of software packages for 'Security constrained Optimal Power flow (SCOPF)'. Latest developments include algorithms for real-time implementation of OPF based on Unlimited Point Algorithm with Message Passing Interface and Parallel Virtual Machine techniquefor distributed implementation which in explains the OPF implementation in real time.

Researchers have been working on Classic Optimal Power flow of Single objective function. However advancements in Power system lead to inevitability of Multi-objective OPF. Much of the work has been done in Multi-objective Optimal Power flow is on the reduction of Generation cost (Minimization of fuel cost) and reduction in Real power losses under given load condition and without violating the bus voltage and other constraints. With growing concerns on environmental protection objective functions like reduction in Environmental impact reduction and Social welfare has gained velocity. A much singular and exciting work has been done by KhaledZeharet al. in (2008), which considers the environmental protection factor viz, Harmful ecological effects caused by the emission of gaseous pollutants like sulfur dioxide (SO2) and nitrogen oxides (NOx) reduction by load adequate distribution between power plants. Much work has been discussed by DeqiangGaet al (2000) about Stability constrained Optimal Power flow; 'transient stability'and other stability constraints like 'voltage stability', 'rotor angle stability' limits, 'tie-line stability' limits and others, has been discussedby DeqiangGanet al., (2000). Increasing demand invited efficent transfer of Power and the development of High power semiconductor devices lead to the introduction of Flexible AC Transmission system (FACTS), first introduced by Hingorani. Optimal Power flow with FACTS modeling has been discussed by Prasad pathyet al.[80] and finally a hardware software co-design for optimal power flow using Field Programmable Gate Array (FPGA) has been reported by Murachet al. in [81].

Widely used objective function is the fuel cost minimization. Some other objective functions are reduction in Environmental impact, Social Welfare factor, Minimizing load shedding (2001), maximizing system performance, reducing magnetic field by LucioIppolitoet al., (2008), minimizing real and reactivepower losses, maximizing power exchange between other operators, minimize heat and loss at generator, minimize transmission losses or can be maximization of reliability and security level of the systemwith thermal constraints, Interface constraints (stability) and Spinning reserve constraints.

The present paper is organized as 7 sections. Section I and Section II deals with the Introduction and Literature overview. Section III gives a view of Optimal Power flow problem origination; Section IV presents a general outlook of the Genetic Algorithm approach. Section VI offers information on the new approach in GA which has been adopted in this paper. Section VII gives comparative results of the new algorithm and summarizes its supremacy over other algorithms.

2.1. Problem Formulation

Optimal Power flow can be defined as a exploration for the finest settings of continuous and discrete variables to attain a certain objective, herein, the minimization of generation cost. In this paper, the approach is formulated by minimizing the Generating cost ($/MW)

$$Minimize\ F\ (z)$$

$$Subject\ to$$

$Hi\ (x,u)\ =\ 0$, where i = 1 to n (Equality constraints)
$Gj\ (x,u)\ \leq\ 0$,where j = 1 to m (Inequality constraints)
where 'u' is the set of controllable quantities, which can be adjusted by the operator like Generator Active Power output, Generator voltage, Transformer settings and Capacitor settings. 'x' is the set of state quantities like voltage magnitude at load bus and Slack bus power and reactive power at each generator & Line Flows.
General Fuel cost objective function is represented as

$$\mathrm{F}(x,u)\ =\ \sum_{i=1}^{Ng}\left(A_i + BP_{gi} + CP_{gi}{}^2\right) \quad (1)$$

where$N_g$is the number of generators including the slack bus. $P_{gi}$is the generated activepower at bus i. A_i, $B_i$and $C_i$are the unit costs curve constants for i^{th}generator. The real splendor of the Optimal power flow lies in minimizing the objective function collectively satisfying the equality constraint and making certain that inequality constraints are not to surpass at any time.

3. Equality Constraints

Optimality of the power cannot be at the cost of essential necessities as the power generated should be able to supply the maximum load and the various losses in transmitting. These constraints are together termed as equality constraints and normally the power flow equation needs to be satisfied

$$0=P_{Gi}-P_{loadi}-V_i\sum_{j=1}^{n}V_j(G_{ij}\cos\delta_{ij}+B_{ij}\sin\delta_{ij}) \quad (2)$$

$$0=Q_{Gi}-Q_{loadi}-V_i\sum_{j=1}^{n}V_j(G_{ij}\sin\delta_{ij}-B_{ij}\cos\delta_{ij}) \quad (3)$$

where, i =1 to n, and 'n' is the number of buses in the system. $P_{Gi}$and Q_{Gi} are active and reactive power generations at bus-i, $P_{loadi}$and $Q_{loadi}$are corresponding active and reactive load demands. Here Fast decoupled (FDC) optimal power flow method is adopted for faster convergence.

4. In-equality Constraints

The inequality constraints selected are: Generator bus upper voltage limits and lower voltage limits ($V_i^{min}\leq V_i\leq V_i^{max}$) at every bus. Active power limits at generator buses ($P_{gi}^{min}\leq$ Pgi $\leq P_{gi}^{max}$), Reactive Power limits at generator buses, Bus injections ($Q_{gi}^{min}\leq$ Qgi $\leq Q_{gi}^{max}$) limits, Tap changing limits, Maximum loadability and size of capacitors are considered under Inequality constraints.

4.1. Constraint Handling

Constraints are handled either by preserving the only one feasible solution or rejecting the solution when there is a violation of the search space. But a compensatory addition to the objective function is adopted, when the violation takes place in the search space making it more feasible. Any infeasible solution can be converted to a probable feasible solution by generating the control variables again.

$$F(x) = \begin{cases} f(x), & if\ x\ is\ feasible \\ New_{f(x)}, & if\ x\ is\ non\ feasible \end{cases} \quad (4)$$

where $New_{f(x)}$, is the value of worst feasible solution together. Much detailed literature on constraint handling using penalty based function is done by vardarajan*et al.* (2008).

3.2. Tables

Captions of tables should be aligned above the tables, in 9-point font, single spacing. The word "Table" and the successive number with the full-stop symbol (".") must be written in bold. Below each table and above its caption should be 1 blank line spacing (10-point). The caption should be separated from the table by one 9-point empty line. Tables must be cited consecutively in the text, e.g. "Table 1".

5. Conventional Approach

Genetic Algorithm (GA) became popular with the much inspired works of John Holland in early 1970s and much of the basic information on algorithms and methods are reported in [7-12]. GA refers to finding solutions in a search space by generating a sequence of individuals, where each one can be a probable solution. The quality of solution is improved by generating newer and better population using genetic operators. Genetic Algorithm proved to be an opportunity when all conventional algorithms had the drawback in modeling discrete variables and of prematurely convergence in a local minimum than at a global minimum due to its parallel processing capabilities [13]. GA refers to stochastic algorithm, with competences of exploring many peaks parallel using probabilistic approach and provides better quality solutions than deterministic approaches. GA doesn't anticipate a much 'well behaved' objective function and allows simple discontinuities and non-linearity which are difficult to model in mathematical programming methods. Hence *'non-linear'*, *'non-convex'*, *'non-differential'* objective functions are found to receive quality solutions using this method. GA exchanges data between the peaks there by much reducing the chances of being trapped in a local minimum. The constraints are modeled as a string of data referred as *'chromosomes'* or *'genotype'*either in *'binary*' or *'real-coded*' and the genetic operators include *'Cross-over'*, *'Mutation'* and *'Reproduction'*. Each parent who is most likely to contain a better fitness solution is nominated for reproduction by exchange of string which emulsifies its characteristics and offspring's are produced which contain strings of both parents which help in exploring newer search spaces.

Crossover can be a single point or multiple point crossovers and a uniform cross-over strategy is implemented in this paper. A sudden and drastic change in the character is introduced in offspring by randomly changing a bit of string to prevent the solutions being trapped in local minima and to prevent all offspring from inheriting similar characteristics. The operator 'reproduction' is based on Darwins' theory of *'survival of fittest'*, which refers the natural theory that only the fittest, survives and other perishes. More generations owe a better qualified solution. Much differentiation of GA with other evolutionary algorithms for power flow applications can be found in [14-21].

6. Proposed Approach

The conventional Genetic Algorithm approach has the serious disadvantage of a blind generation of initial population, which ended in larger search space area, prolonged computation time and mediocre solutions. The inferiorly fit individuals too actively participate which leads to higher computational time for evaluation and convergence into global solution. As the mutation probability is constant in conventional GA for all the individuals, the chances of good fit individual getting distorted and degraded to a lower band are more. Here a novel approach is adapted in selection of initial population and in Genetic Operators which are explained in detail in the following sessions.

6.1. Representation of Individual

Each of the strings in the population represents a probable solution. Depended on either binary coded or real coded, the strings are designed, as a set of filaments which moulds as chromosomes. The size of the chromosome is decided in concurrence with the accuracy of the solution required and each variable is allotted specific binary capacity to represent themselves, which in-turn with all the variables together form the string representing the chromosome. Each individual in the chromosomes consists of control variables and discrete variables represented as,

$$Ind.string = [(control\ variables\ 'c'), (discrete\ variables\ 'd')]$$

Control variables are modeled as being continuously varying, are narrowed to the lower and higher limits while discrete variables are sculpted by taking particular step size. Continuous controls taking values in the interval $[u_i^{min}, u_i^{max}]$

$$u_i = u_i^{min} + \left(\frac{u_i^{max} - u_i^{min}}{2^{li} - 1} \right) DV_i \tag{5}$$

Discrete controls taking M values $u_i^1, u_i^2 \ldots, u_i^M$

$u_i = u_i^m$, with

$$m = \mathrm{int}\left[\frac{M}{2^{li}} DV_i + 1.5 \right] \tag{6}$$

whereDV_i is the decoded value of control variable u_i from li bits and 'li' is the gene length (number of bits) used for encoding the variable $u_i$for i^{th} control variable. Each chromosome represents a set of control variables.

6.2. Variables

Variables namely continuous control variables and discrete control variables are modeled as below in fig. 1. The continuous control variables include generator active power outputs except slack bus power, generator voltage magnitudes, and discrete control variables include transformer tap settings and switchable shunt devices.

P_{G2} .... P_{NG} $V_{G1...}$ V_{NG} $T_{1...}$ ......T_{NT} $b_{1....}b_{NC}$

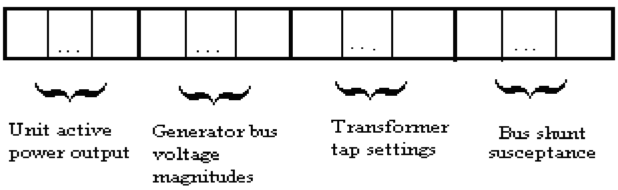


Figure. 1. Encoding design of a chromosome

6.3. Expert Based Initial Generation

In conventional GA, the entire population is generated randomly. In proposed method, chromosomes are generated randomly as customary in the first generation and based on their fitness the most significant bits are transferred to lowest fitness of chromosome as illustrated below.

Chromosome$_1$:

Most Significant bits

1 0 1 1 0 0 1 1

Chromosome$_2$:

1 1 0 0 0 1 0 0

Most Significant bits

Figure. 2a. Conventional Generation method

The decoded value depends on most significant bits and hence, the most significant bits of chromosome having high fitness are transferred to chromosome which is having low fitness. In the Fig. 2, the first chromosome has a decoded value of 0.7019 and the second chromosome offers 0.7686. This can be illustrated using simple Sin(x) maximization problem, consists of x limits from 0 to 180, a string length of 8 and the fitness of Ch_1 = 0.8104 and Ch_2 = 0.6715. Then,

$$\text{Fit}(Ch_2) < \text{Fit}(Ch_1)$$

The most significant bits of Ch_2 are replaced with the most significant bits of Ch_1 produce a chromosome as below.

Chromosome$_{1\ (New)}$:

Most Significant bits

1 0 1 1 0 0 1 1

Chromosome$_{2\ (New)}$:

1 0 1 1 0 1 0 0

Most Significant bits

Figure. 2b. Proposed Initial Generation method

The direct fitness values for the new chromosomes are 0.8104 and 0.803 respectively which endorses the considerable improvement using the new technique, which is adopted throughout in the proposed algorithm.

The algorithm for n chromosomes is as below:

A. Generate two chromosomes calculate the decoded value and fitness of each chromosome.
B. Based on fitness, change most significant bits as explained above
C. Begin i=3 to p_{size}(= n)
   Ch(j) = rand int (j, string length)
D. Calculate fitness of i^{th} Chromosome.
E. If fit (i) > fit (i-1), change most significant of previous chromosomes with i^{th} chromosomes, ELSE

F. Change Ch(i) most significant bits with Ch(i-1)
G. End of i^{th} loop

This is how an initial population with better fit values is generated without much additional computational burden. This aspect undoubtedly improves the convergence of GA.

6.4. Fitness and Probability

Fitness is derived from the evaluated objective function of the available chromosomes. Here, the objective is a minimization problem and hence the fitness is the reciprocal of evaluated objective function, as we tend to minimize the fuel cost. If any constraint violates, the fitness function is modified using constraint handling method which is discussed in Section III. In this approach proper penalty factors are to be selected judiciously by the operator. Operators experience & Suitability of the selected penalty factors will have significant influence on the speed of convergence. To overcome this disadvantage a method reported in [84] is used. The $New_{f(x)}$, is the value of worst feasible (least fitness) solution together with the overall constraint violation of solution. The overall constraint violation integer is the sum of the total inequality constraints violated.

6.5. Elitism

Elitism prevents from losing best individual received so far as we move to further reproduction. Depending upon the fitness values, 20% of the total population are selected as best fit and is promoted to next generation. Before implementing the elitism, arrange the chromosomes in descending order.

6.6. Chromosome Selection

The Roulette Wheel technique is adapted for the selection of Parents. The cumulative fitness (Fit_{Sum}) is evaluated for the chromosomes, after arranging in descending order according to the fitness. A random number is generated in-between 0 and on order of their fitness values. The cumulative sum of the chromosomes starting from 1^{st} chromosome is compared with the generated random number and whenever this sum exceeds the random value, then that chromosome is selected as parent. In existing approach of parent selection by Roulette Wheel technique, there is a possibility of random number, generated between 0 to 'fitsum', may fall near to 'fitsum' and there is a chance to pick up the chromosome with poor fit value as a parent chromosome. This causes slow convergence in next generation of GA & may take more solution time. Further observation is that after 4 to 5 generations, most of the additional iterations or generations are required to force the dejected chromosomes to reach better fit.

These drawbacks can be considerably reduced in the proposed approach. In this approach, after the minimum 3 to 4 iterations, a random numbers is generated between 0 to $(fitsum)/2$ and the process is continued as usual. This could help to pick up chromosome with better fit as 'parent chromosome' in new iterations. This would force the algorithm to have fast convergence without any sacrifice on the quality or accuracy of final solution.

6.7. Chromosome and Mutation

Mutations are essential to develop more athletic generations and are induced by a sudden change/inversion in a bit of chromosome. Cross over allows transferring the parental traits to the offspring's by partially transferring the genes. Crossover can be a uniform crossover, random cross over; single point or multiple point crossovers. A uniform cross-over is adapted in this algorithm. The cross over probability (P_c) is limited from 0.5 to 1 and Mutation probability (P_m) from 0.001 to 0.05

In the conventional approach, the probabilities of crossover and mutation are constant then solution with high fitness and low fitness values are subjected to same level of mutation and crossover, which leads to the convergence of the solution in a local optimum.

The above problem is overcome by changing P_c and P_m depending on their fitness values. For high fitness the Pc and Pm must be low and vice-versa. Then the P_C can be taken as

$$Pc = K_1(f_{max} - f')/(f_{max} - f_{avg}) \quad (7)$$

where f is highest fitness of two chromosomes selected, $f_{max}$is the maximum fitness and $f_{avg}$is the average fitness. Similarly the P_m is also taken as

$$Pm = K_2(f_{max} - f)/(f_{max} - f_{avg}) \quad (8)$$

where f is the fitness of chromosome selected.

This two equations will offer P_C and $P_m$more appropriately.

The improved strategy is,

a. when $f'=f=f_{max}$ then Pc = Pm = zero
b. If $f'=f = f_{avg}$ P_c=k, and P_m=k_2

Now, if f <f_{avg} and f <f_{avg} then P_c and P_m might be of larger value, a modified equation is formed as

$$Pc = K_1(f_{max} - f')/(f_{max} - f_{avg}); \quad f' \geq f_{avg} \ \ldots\ldots \quad (9)$$

$$Pc = k_3,\ f' < f_{avg}$$

$$Pm = K_2(f_{max} - f)/(f_{max} - f_{avg});\ f \geq f_{avg} \ \ldots\ldots \quad (10)$$

$$Pm = k_4,\ f < f_{avg}$$

k_1, k_2,k_3,k_4 values are 1, 0.5, 1, 0.5 respectively [22]. When fitness value tend to less than or equal to f_{avg},chromosomesare enforced to undergo crossover and mutation. When the individual fitness of each chromosome attains the maximum fitness, then cross over P_C and P_m will tend to be zero, in such case, the global optimal solution may not be attained, which necessitates the modification of P_C and P_m . If $P_{C1,}$ $P_{C2;}$ and $P_{m1,}$ P_{m2} are values evaluated for two selected chromosomes (9) and (10), then the modified values are given by

$$Pc(new) = P_{c1} - (P_{c1} - P_{c2})(f_{max} - f)/(f_{max} - f_{avg}); \quad \text{where, } f \geq f_{avg} \quad (11)$$

$P_{Cnew} = P_{C1,}$ where, f <f_{avg}

$$Pm(new) = P_{m1} - (P_{m1} - P_{m2})(f_{max} - f')/(f_{max} - f_{avg}) \quad (12)$$

where $f = (f1 + f2)/2$ and f_1, f_2 are fitness of first and second chromosomes. The above approach could avoid chance of reaching local optimum & allow it to reach global optimum.

6.8. Shunt Capacitor Placement using Quadratic Power Flow

The converged voltages, phase angles and power flows at each bus are obtained using the Quadratic Power Flow Method [23]. The optimal locations of the capacitors are found using the Quadratic Fast Decoupled Load flow based index (FDLFI) values.
The active and reactive power injections at bus-p bus are given by eqns.

$$P_p = \sum_{q=1}^{n} V_p V_q Y_{pq} \cos(\delta_{pq} - \theta_{pq}) \quad (13)$$

$$Q_p = \sum_{q=1}^{n} V_p V_q Y_{pq} \sin(\delta_{pq} - \theta_{pq}) \quad (14)$$

where $\delta_{pq} = \delta_p - \delta_q$.

$$P_p + Q_p = \sum_{q=1,\neq p}^{n} V_p V_q Y_{pq} \cos(\delta_{pq} - \theta_{pq}) + \sum_{q=1,\neq p}^{n} V_p V_q Y_{pq} \sin(\delta_{pq} - \theta_{pq}) + V_p^2 (G_{pp} - B_{pp}) \quad (15)$$

This is of the form

$$AV_p^2 + BV_p + C = 0 \quad (16)$$

where $A = (G_{pp} - B_{pp})$;

$$B = \sum_{q=1,\neq p}^{n} V_q Y_{pq} \cos(\delta_{pq} - \theta_{pq}) + \sum_{q=1,\neq p}^{n} V_q Y_{pq} \sin(\delta_{pq} - \theta_{pq}) \quad (17)$$

$$C = -(P_p + Q_p);\ P_p = P_{Gp} - P_{loadp};\ Q_p = Q_{Gp} - Q_{loadp} \quad (18)$$

The following sets of equations are adopted for the Quadratic Fast Decoupled Load Flow method.

$$[\Delta P/|V|] = [B'][\Delta\delta] \text{ from FDLF model} \quad (19)$$

$$AV_p^2 + BV_p + C = 0 \quad (20)$$

Eqn. (19) provides Phase angle corrections bus voltage angles and with updated angles and (20) provides bus voltage magnitudes. Here, load flow solution exists only if the 'discriminant' is greater than or equal to zero which implies that (B^2-4AC $\geq$ 0), which in turn serves as a voltage stability indicator (VSI), determining the proximity of the system to voltage collapse. A high value of (B^2-4AC $\geq$ 0) indicates a stable system and low value implies a voltage collapse. Further, the voltage stability index is obtained just as an integral part of the load flow solution and no additional calculation is required for determination of voltage stability indices.

Voltage stability Margin (VSM) = B^2- 4AC (21)

Voltage Stability Index = (VSM) / (Max (VSM)) (22)

The index tends to vary from 0 to 1 and the bus with minimum index is found to be the best location for placing the shunt capacitor.

6.9. Termination Condition

The algorithm is designed to terminate when the fitness of all chromosomes are equal or when the maximum iteration limit is attained. A detailed flow chart of the proposed algorithm is given in fig. 3

7. Algorithm and Simulation

The proposed Genetic Algorithm (PGA) is tested on standard IEEE 14 and 30 bus systems and are compared with Simple Genetic algorithm (SGA) and Particle Swarm Optimization (PSO) algorithm. IEEE 14 bus test system consists of 5 generators, 20 lines, 3 transformers, 1 shunt device and a total active power load of 259 MW. IEEE standard 30 bus test system comprises of 6 generators (including slack bus), 30 buses, 41 branches, 4 tap changing transformers, 2 shunt reactors, 5 shunt capacitors placed at optimal location (after Base Case Power Flow) and with a load of 283.14 MW. The complete algorithm has been implemented in Matlab platform using a C2D 2 GHz processor.
On comparative analysis with available algorithms, the proposed method is proved to be a very promising development. Detailed results are given in following Tables I, II and III.

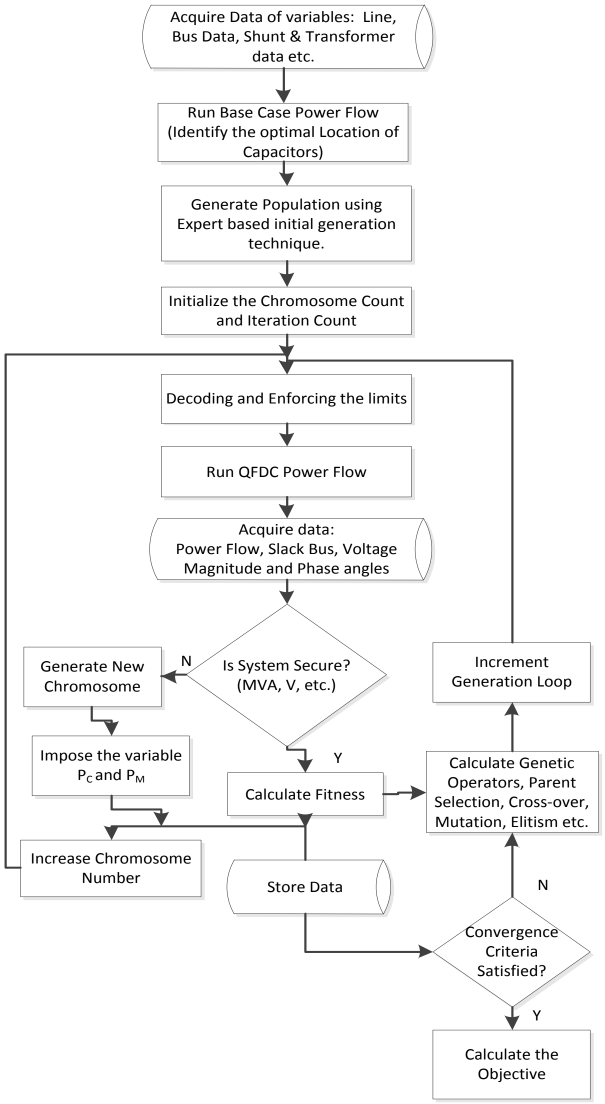


Figure. 3. Basic Flow Chart of the Process

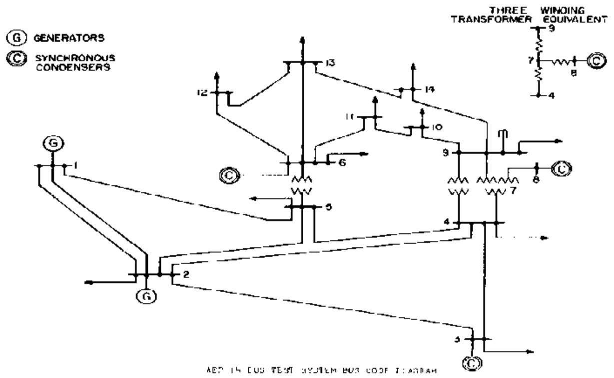
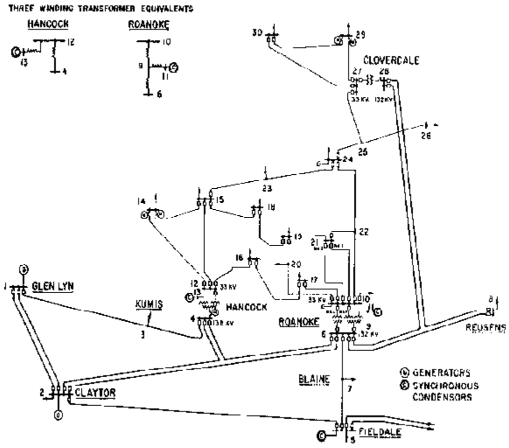


Figure. 4. IEEE 14 Bus test system
(Courtesy: University of Washington)



. Fig. 5 IEEE 30 Bus test system
(Courtesy: University of Washington)

Table 1. Results on a standard IEEE 30 bus sytem

System (30 bus)	SGA-VP*	SGA	PSO+	PGA	PGAVP*
Time (secs)	69.43	47.39	36.26	29.96	21.17
Iterations	73	41	84	24	21
Time/Iter	0.95	0.91	0.431	1.25	0.53
Fuel Cost ($/MW)	802.85	802.88	802.64	802.6	802.96

*SGA-VP: simple GA without Variable probability
*PGAVP: proposed GA without variable probability
+ Termination Criteria as of GA

Table 2. Results with various N_{pop}

N_{pop}	$P_{G2(MW)}$	$P_{G5(MW)}$	$P_{G8(MW)}$	$P_{G11(MW)}$	$P_{13(MW)}$	Loss (MW)
100	49.17	20.87	23.18	11.95	12.37	9.37
60	48.96	22.01	21.35	10.96	12	9.4
30	48.92	20.52	26.65	13.74	12.85	9.47

Table 3. Comparison using various Algorithms

Control Variables	Base Case	SGA	PSO	PGA
PG_2 (MW)	80	49.34	48.83	48.96
PG_5	50	21.93	21.13	22.01
PG_8	20	22.96	20.27	21.35
PG_{11}	20	12.78	12.37	10.96
PG_{13}	20	12.1	12.8	12
VG_1(pu)	1	1.05	1.05	1.05
VG_2	1	1.01	1.044	1.06
VG_5	1	1.09	1.043	0.99
VG_8	1	1.04	1	0.972
VG_{11}	1	1.08	1.02	1.02
VG_{13}	1	1.02	1.01	1.01
$Tap_{6,9}$(pu)	1	0.96	0.9	1.02
$Tap_{6,10}$	1	1.05	1.1	0.92

$Tap_{4,12}$	1	1.012	1	0.95
$Tap_{27,28}$	1	1.02	1.025	1.03
$Shunt_{14}$(pu)	0	0.02	0.03	0.02
$Shunt_{16}$	0	0.04	0.05	0.01
$Shunt_{23}$	0	0.02	0.04	0.03
$Shunt_{25}$	0	0.01	0.01	0.01
$Shunt_{26}$	0	0.03	0.02	0.01
$Shunt_{29}$	0	0.01	0.05	0.01
$Shunt_{30}$	0	0.01	0.02	0.02
Losses	6.1787	9.66	9.51	9.4
(MW)				
Cost ($/MW)	902.92	803.15	802.64	802.66

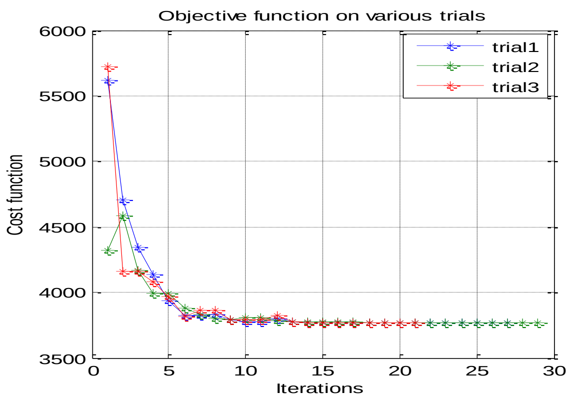


Fig. 6 Objective function on various trials in IEEE 14 bus system

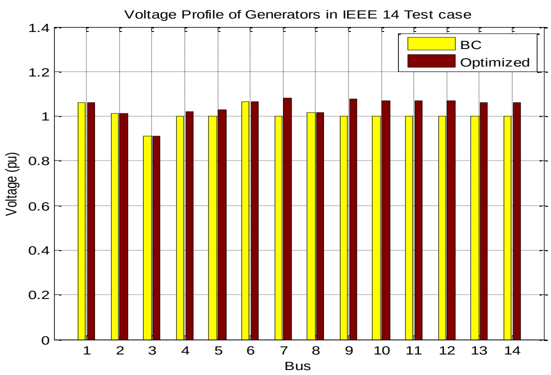


Fig. 7 Voltage Profile before and after Optimization in IEEE 14 bus system

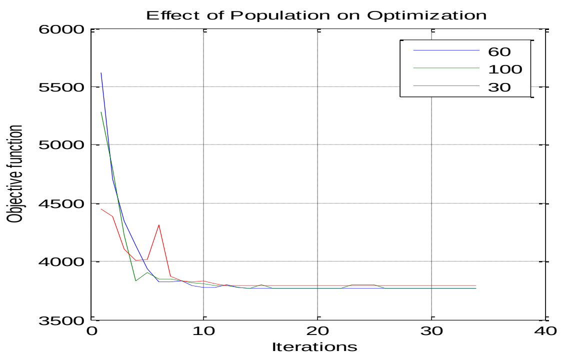


Fig. 8 Voltage Profile before and after Optimization in IEEE 14 bus system

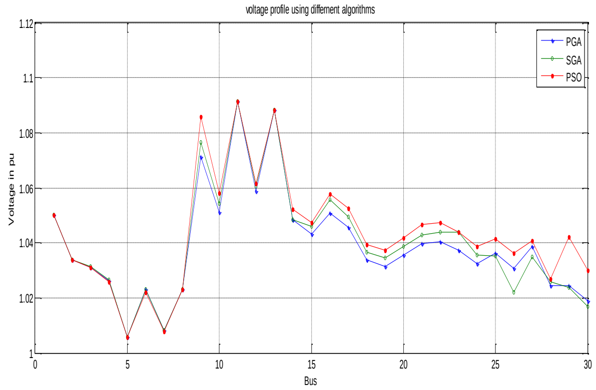


Fig. 9 Voltage Profile of IEEE 30 bus system using PGA, SGA and PSO techniques

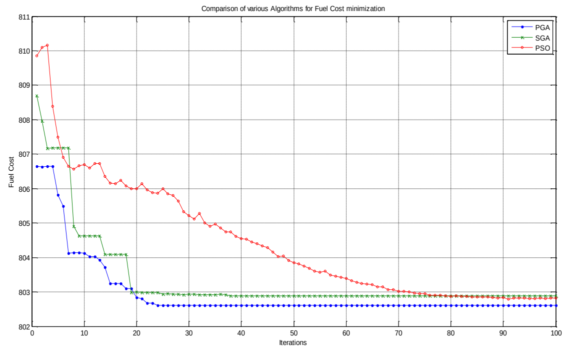


Fig. 10 Fuel cost minimization for IEEE 30 bus system using PGA, SGA and PSO techniques

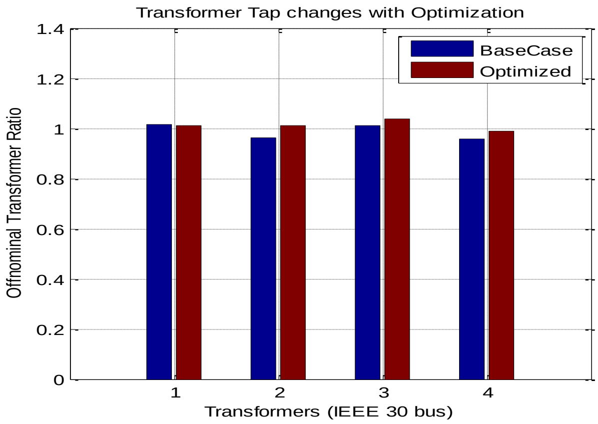


Fig. 11 Transformer Tap settings with Optimization

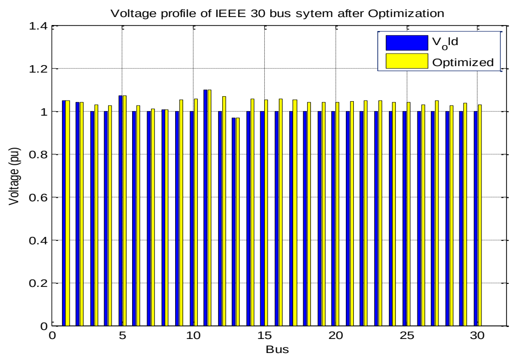


Fig. 12 Voltage Profile of 30 Bus before and after Optimization

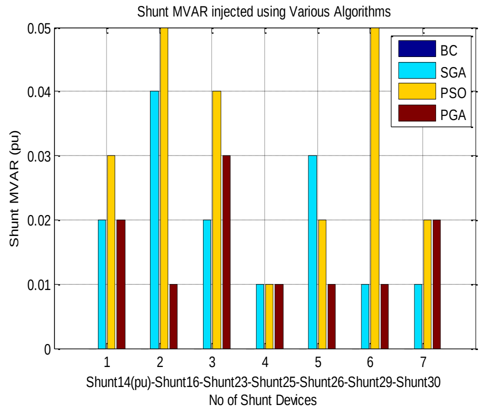


Fig. 13 Shunt MVAR injected using various algorithms

The proposed algorithm offers considerable savings in the computation time to the tune of 3x times. Conventional Genetic Algorithm without variable probability has converged at lowest iterations of 21 generations and with variable probability has converged in 24 generations in 0.53 and 1.25 seconds respectively, which shows a considerable superiority on other algorithms on PSO and SGA. Variation of Active Power Generation using different Population size has been discussed in Table 6, and it's found that a Population size of 100 provides the lowest losses, but computationally intense. Comparison of various continuous variables and discrete variables are given in Table 7. The performance of the proposed GA for various trials is shown in Fig. 6 for a population size of 60. The voltage profile of generators of IEEE 14 and 30 bus test system before and after Optimization is given in Fig. 7 and Fig. 12 respectively. The effect of Population size is illustrated in Fig 8 and its found that with increase in population size, better optimization is achieved, but at the cost of higher computation power and time. Voltage profile and Cost minimization of IEEE 30 bus test system using PGA, PSO and SGA is illustrated in Fig. 9 and Fig. 10 respectively and it's found that maximum cost minimization is achieved using the proposed algorithm. Off-nominal transformer ratios for base case and Optimized case are illustrated in Fig. 11. The optimum location of the shunt devices are found using VSI technique and Shunt MVARs injected into various buses using different Optimization techniques are illustrated in Fig. 13.

8. Conclusions

In this paper, an attempt has been made to propose a new notion in generating an improved initial population for GA, involving an expert based technique instead of a blind conventional method for initial population generation. An adaptive probability for Crossover and Mutation probability has been tested on standard OPF problem. Further, discussions on developments in Optimal Power flow, its challenges are made in detail. An effective suggestion has been made in selecting parent-1 & Parent-2 using roulette wheel technique after minimal iterations with proposed initial population. The objective function minimizes the Generator Fuel cost while satisfying all the security and necessary constraints. The results of Proposed Genetic Algorithm on IEEE 14 and 30 bus test system are compared with Simple Genetic Algorithm and Particle Swarm optimization techniques for same test composition. Results revealed that the proposed algorithms superiority over other algorithms and is promising for implementation on numerous further applications comprising of continuous and discrete variables. The PGA is found to demonstrate an enhanced performance in minimizing the fuel cost, power loss and computation time and converges in lowest number of iterations.

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